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Improvement of transient stability in an SMIB system through PSS optimization using CMA-ES.

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ABSTRACT: *In this paper, we focused on improving the damping of oscillations generated by the action of voltage regulators in the electrical system. To achieve this, we considered an SMIB system and designed the corresponding Heffron-Phillips model. We then integrated the PSS model into the obtained linearized model. Using this model, we established an objective function based on the damping factor and the damping ratio of the eigenvalues. This objective function was then minimized using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimization method to obtain the PSS parameters. The analysis of the eigenvalues, damping ratios, and machine variable curves demonstrated the effectiveness of the PSS obtained through CMA-ES compared to the conventional PSS.*

Keywords*: Single Machine Infinite Bus (SMIB), Power System Stabilizer, CMA-ES*

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I. INTRODUCTION

Nowadays, the devices we use in daily life are almost all powered by electricity. As a result, the demand for electricity by households is steadily increasing. For electricity companies, meeting this growing demand requires an increase in production, as well as in transmission and distribution infrastructure. However, managing a large-scale power system is technically challenging, as companies have obligations to maintain the quality of the electricity supplied to users. On an international scale, standardization organizations such as the IEC (International Electrotechnical Commission) and ISO (International Organization for Standardization) are responsible for establishing quality standards based on key criteria such as frequency, voltage, harmonics, and service continuity. Typically, these organizations impose limit ranges for these parameters that electricity companies must not exceed. Since an electrical system is a dynamic multivariable system, where one variable influences others, ensuring compliance with these standards is not always straightforward.

It is known that in an electrical system, the balance between the active and reactive power produced by the generators and consumed by the loads connected to the system ensures the stability of voltage and frequency.

To meet voltage standards, a device called the Automatic Voltage Regulator (AVR) is inserted into the excitation systems of synchronous generators to adjust the reactive power produced or consumed in order to keep the output voltage close to a setpoint value. While these regulators play an important role in voltage control, they also have adverse effects on the system as a whole. The action of AVRs can induce oscillatory instability in the electrical system. This type of instability is characterized by oscillations typically within a frequency range of 0.1 to 0.8 Hz [1], and these oscillations can persist or even grow in amplitude. To mitigate or even eliminate this effect, additional stabilizing signals from devices called Power System Stabilizers (PSS) have been added to the excitation systems.

Due to their cost-effectiveness and efficiency, Power System Stabilizers (PSS) are the most effective solution for mitigating the negative effects of Automatic Voltage Regulators (AVR). However, the performance of these devices is highly dependent on their parameter settings [2]. Numerous methods have been proposed in the literature to adjust the parameters of PSS [2]. These methods, based on the linearized model of the system, can be classified into two categories:

The first category involves analyzing the system's eigenvalues. In these cases, the PSS parameters are designed using the linearized model of the system around a nominal operating point [3].
Numerous methods have been proposed in the literature for tuning the parameters of Power System Stabilizers (PSS) [2].
These methods, based on the system's linearized model, can be classified into two main categories:

- Phase compensation method,

- Residue method,
- Pole placement method.

The second category involves defining objective functions and optimizing those using metaheuristic methods to determine the PSS parameters. The most commonly used objective functions are based on: damping factors (real part of the eigenvalues) [1], the damping rate of the eigenvalues [4] [5], Integral of Square Error (ISE) [6], Integral of Time-weighted Absolute value of Error (ITAE) [3], and Integral of Absolute Error (IAE) [7]. Other studies combine some of these objective functions to create multi-objective functions. The optimization methods already explored for finding the optimal values for these functions include:

- Genetic Algorithm [1], [2], [3], [8]
- Particle Swarm Optimization [4], [5], [6]
- Cuckoo Search [7]

In this paper, the research objective is to find a more efficient PSS, specifically one that quickly dampens oscillations. To achieve this, the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimization method is used to optimize objective functions based on the damping factor and the damping rate of the eigenvalues in order to determine the PSS parameters. The results obtained are then compared with the results from the same system with a PSS calculated using the phase compensation method, as well as with the system without a PSS.

II. METHODOLOGY

2.1- Modeling of the SMIB system

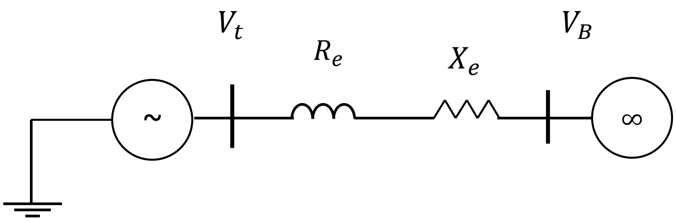

Fig. 1 SMIB System

To analyze the transient stability of an electrical network, it is crucial to simplify the network by representing it with an equivalent model. This model consists of a synchronous generator connected to an infinite bus through a transmission line with an impedance Z. This impedance corresponds to the Thevenin equivalent impedance as observed at the terminals of the synchronous generator [9]. In this model, the voltage magnitude and the frequency of the infinite bus are assumed to be constant [4]. The single-machine infinite bus system is illustrated in Fig. 1. The dynamics of the generator and its excitation system are modeled using the differential equations presented below [10]:

$$\begin{cases} \frac{d\delta}{dt} = \omega - \omega_s \\ \frac{d\omega}{dt} = \frac{\omega_s}{2H}(P_m - P_e - D\omega) \\ \frac{dE'_q}{dt} = \frac{1}{T'_{qo}}\left((x_d - x'_d)I_d + E'_q - E_{fd}\right) \\ \frac{dE_{fd}}{dt} = \frac{1}{T_A}\left(-E_{fd} + K_A\left(V_{ref} - V_t\right)\right) \end{cases} \quad (1)$$

The generator and excitation system dynamics are inherently nonlinear. However, the system can be simplified into a time-invariant linear form by linearizing it around a steady-state operating point. Following this linearization, the system dynamics can be expressed in state-space form as shown below [11].

$$\frac{dx(t)}{dt} = A.x(t) + B.u(t) \quad (2)$$

Where $x(t)$ is the state vector and $u(t)$ is the input stabilizing signal [10].

$$x(t) = [\Delta\delta \quad \Delta\omega \quad \Delta E'_q \quad \Delta E_{fd}]^T \tag{3}$$

$$u(t) = [\Delta V_{ref}] \tag{4}$$

The expression of matrix A is [10]:

$$A = \begin{bmatrix} 0 & \omega & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 \\ -\frac{K_4}{T'_{d0}} & 0 & -\frac{1}{K_3 T'_{d0}} & \frac{1}{T'_{d0}} \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & \frac{K_A}{T_A} \end{bmatrix}^T \tag{6}$$

Equation (2) represents a fourth order system with as state variable: rotor speed ($\Delta\omega$), load angle ($\Delta\delta$), internal voltage ($\Delta E'_q$) and field voltage (ΔE_{fd}). The block diagram of the linearized system, more often known as the Heffron-Phillips model of the SMIB system, is shown in Fig.4. Here the input to the system is the AVR reference voltage and the output is the rotor speed deviation.
The constants (K1-K6) are called Heffron-Phillips constants, and are computed in [9].

2.2- Modeling of the PSS

The Power System Stabilizer (PSS) is a control device used in power systems to enhance stability by damping low-frequency electromechanical oscillations that can arise due to disturbances like load changes or faults. It operates by monitoring signals such as rotor speed, frequency, or power output, processing them to generate a stabilizing signal that is fed into the generator's excitation system. This signal adjusts the excitation voltage to modulate the generator's output power and electromagnetic torque, counteracting the oscillations. By improving damping, the PSS helps maintain synchronism among generators, enhances dynamic stability, and reduces the risk of instability in the power grid.
There are different types of PSS: Proportional-Integral (PI) PSS, Proportional-Integral-Derivative (PID) PSS and Lead-Lag controller based PSS.

The PSS block structure comprises a dynamic gain to enhance damping, a Washout block functioning as a high-pass filter to minimize steady-state terminal voltage errors, and a lead-lag compensator blocks that provide additional phase shifting to reduce the mismatch between electrical torque and excitation[7] and finally the limiter blocks limit the amplitude of the control signals[4]. The PSSs take the change in generator angular frequency ($\Delta\omega$) as the inputs and the PSS output signalΔV_{PSS}, is then fed as a secondary input to the AVR loop, this structure is shown in Fig.2[4]

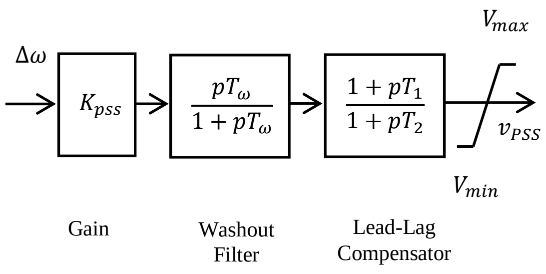

Fig. 2 Structure of lead-lag PSS

Where K_{PSS} is PSS gain, T_w is wash out time constant, T_1 and $T_2$are lead-lag time constants.
The transfer function of the Power System Stabilizer (PSS) is given by [1]:

$$v_{PSS} = K_{PSS} \frac{pT_\omega}{1+pT_\omega} \frac{1+pT_1}{1+pT_2} . \Delta\omega \tag{7}$$

2.3-Combined SMIB model with PSS

The washout filter stage is excluded as its primary purpose is to eliminate the steady-state error, which does not influence the design process. The transfer function of the PSS is combined with the linearized SMIB model in Equation (2) to derive the state-space representation:

$$\frac{dx(t)}{dt} = A_{pss}. x(t) + B_{pss}. u(t) \tag{8}$$

Where the system A-matrix of this model is given by the equation (9) below [4] :

$$A_{pss} = \begin{bmatrix} 0 & \omega & 0 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 & 0 \\ -\frac{K_4}{T'_{d0}} & 0 & -\frac{1}{T'_{d0}K_3} & \frac{1}{T'_{d0}} & 0 \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & 0 \\ -\frac{K_{PSS}. K_1. T_1}{M. T_2} & \frac{K_{PSS}}{T_2} - \frac{K_{PSS}. D. T_1}{M. T_2} & -\frac{K_{PSS}. K_2. T_1}{M. T_2} & 0 & -\frac{1}{T_2} \end{bmatrix} \tag{9}$$

2.4- Formulation of the PSS optimization problem

Considering the system described by equation (8), for an oscillatory mode associated with a pair of complex conjugate eigenvalues $\lambda = \sigma \pm j\omega$, the following terms characterize the dynamic behavior of the system :

σ : the real part of the eigenvalue, referred to as the damping factor.

ω : the imaginary part, representing the frequency of the oscillatory component.

ζ : the damping ratio

$$\zeta = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}} \tag{10}$$

- The damping ratio ζ represents the system's ability to attenuate oscillations. A low ζ indicates that oscillations persist for a longer time, whereas a high ζ means the oscillations decay rapidly.
- The real part of the eigenvalue σ indicates how quickly the amplitude of oscillations decreases over time, influencing the system's return to equilibrium after a disturbance. A small σ (close to zero) signifies weak damping, causing oscillations to persist longer, while a larger σ (more negative) represents stronger damping, leading to a faster decay of the oscillation amplitude.

To improve the damping of the system, we adopt the following objective function[1] , [4] :

$$f_1 = \max(\sigma_i) \tag{11}$$
$$f_2 = \max(-\zeta_i) \tag{12}$$

We obtain two objective functions$f_1$and f_2. To simplify the study, these two objective functions are added to have a single objective function, we obtain:

$$f = \alpha. f_1 + \beta. f_2 \tag{13}$$

αandβ are sensitivity coefficients.

The objective function is finally:

$$\text{Minimize } f \tag{14}$$

With the constraints [12]:

$$\begin{gathered} K_{PSS}^{min} < K_{PSS} < K_{PSS}^{max} \\ T_1^{min} < T_1 < T_1^{max} \\ T_2^{min} < T_2 < T_2^{max} \end{gathered} \tag{15}$$

Since the washout filter should not have any effect on phase shift or gain at the oscillating frequency, it can be achieved by choosing a large value of T_w so that sT_w is much larger than unity[4], [12].

2.5-CMA-ES Optimization method

Optimization is a key area in engineering and science, focused on identifying the best possible solutions within a given search space. Optimization problems are generally categorized based on the nature of the functions to be optimized and the constraints to be satisfied. Among these categories, we distinguish in particular [13]:

- The complexity of the objective function, such as linearity, convexity, continuity, availability of the gradient, or the presence of multiple local minima.
- The number of objective functions to satisfy simultaneously (multi-objective optimization).
- The presence of constraints, where strict restrictions define the boundaries of the search space.

Traditional deterministic methods are used to solve optimization problems; however, these methods are inefficient or inapplicable for certain complex problems [13].

Stochastic methods are then necessary to address these issues. These stochastic methods use random sampling or probabilistic processes to explore the solution space, helping to avoid, for example, local minima.

In this context, evolutionary algorithms have gained popularity for solving difficult problems due to their approach based on principles inspired by natural evolution [14]. The most commonly used evolutionary algorithms are [14]: Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, etc. Among these algorithms, CMA-ES (Covariance Matrix Adaptation Evolution Strategy), introduced by Nikolaus Hansen and Andreas Ostermeier in the late 1990s, is recognized as one of the most robust and efficient methods [15].

2.5.1- Principle of CMA-ES optimization

The CMA-ES (Covariance Matrix Adaptation Evolution Strategy) is a stochastic, population-based optimization algorithm designed for solving complex, non-linear, and non-convex optimization problems in continuous domains [15]. It works by iteratively sampling candidate solutions from a multivariate Gaussian distribution, which is adapted over time based on the fitness of previously sampled solutions [15]. The adaptation involves updating the covariance matrix of the distribution to learn the shape of the objective function and steer the search toward promising regions. The algorithm also adjusts a global step size to balance exploration and exploitation. CMA-ES is particularly effective for high-dimensional and difficult optimization problems where gradient information is unavailable. [15]

2.5.2- Stage of the optimization process

- Initialization:

The algorithm starts with [16]:

An initial mean m_0, which is often an approximate estimate of the optimum.

An initial covariance matrix $C_0 = I$ (identity matrix), indicating that the search is isotropic.

An initial standard deviation σ_0, defining the size of the initial mutations.

A population size λ, which determines the number of candidate points generated at each iteration.

- Population Generation:

At each iteration d, a population $x_i^{(d)}$ of λ candidate is generated by sampling the Gaussian distribution [15]:

$$x_i^{(d)} = m^{(d)} + \sigma^{(d)}.\, y_i^{(d)} \tag{16}$$

Where: $y_i^{(d)} \sim \mathcal{N}\left(0, C^{(d)}\right)$

Each candidate point $x_i^{(d)}$ is a perturbation of the current mean $m^{(d)}$, with deformations guided by σ and C.

- Evaluation of candidate populations:

The points $x_i^{(d)}$ are evaluated using the objective function f. The objective is to minimize $f(x)$. The points are then ranked based on performance, so that [16]:

$$f\left(x_1^{(d)}\right) \leq f\left(x_2^{(d)}\right) \leq \cdots \leq f\left(x_\lambda^{(d)}\right)$$

- Selection of child populations:

Select the μ best individuals from the population based on the objective function values (individuals with the lowest objective function values are preferred) [16].

$$\left\{x_1^{(d)}, \ldots, x_\mu^{(d)}\right\} / f\left(x_1^{(d)}\right) \leq f\left(x_2^{(d)}\right) \leq \cdots \leq f\left(x_\mu^{(d)}\right)$$

- Update mean:
The new mean $m^{(d+1)}$ is calculated as a weighted combination of the μ offspring populations [17]:

$$m^{(d+1)} = \sum_{i=1}^{\mu} w_i . x_i^{(d)} \tag{17}$$

Where: $\sum_{i=1}^{\mu} w_i = 1$ and $w_i \geq 0$
The weights w_i favor the best individuals (typically $w_1 > w_2 > \cdots > w_\mu$).

- Update Evolution path
Update the evolution path for the covariance matrix: the path p_c keeps track of recent steps of the mean vector, adjusted by the step size. It shows the direction the center of the distribution is moving over time[15].

$$p_c^{(d+1)} = (1 - c_c)p_c^{(d)} + h_\sigma \left(\sqrt{c_c(2 - c_c)\mu_{eff}}\right)\left(\frac{m^{(d+1)} - m^{(d)}}{\sigma^{(d)}}\right) \tag{18}$$

Update the evolution path for cumulative step size adaptation: The path vector p_σ dynamically adjusts the step size. If p_σ is too long, the step size is reduced; if too short, it is increased. This helps the algorithm adapt to the local search space conditions[15].

$$p_\sigma^{(d+1)} = (1 - c_\sigma)p_\sigma^{(d)} + \left(\sqrt{c_\sigma(2 - c_\sigma)\mu_{eff}}\right) C^{-\frac{1}{2}}\left(\frac{m^{(d+1)} - m^{(d)}}{\sigma^{(d)}}\right) \tag{19}$$

- Update step size:
The standard deviation σ controls the step size, balancing exploration and exploitation in the solution space. A larger σ means sampled points are farther from the current mean m, encouraging exploration. Conversely, a smaller σ results in smaller mutations, focusing on exploiting areas near the current mean [15].

$$\sigma^{(d+1)} = \sigma^{(d)} . \exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\|p_\sigma^{(d+1)}\|}{E\|\mathcal{N}(0, I)\|}\right) - 1\right) \tag{20}$$

- Update Covariance Matrix
To update the covariance matrix, we combine the previous matrix with two new parts: one part based on the evolution path (p_c), and another part based on the best steps from the current population [15].

$$C_{k+1} = (1 - c_1 - c_\mu)C_k + c_1 p_c p_c^T + c_\mu \sum_{i=1}^{\mu} w_i y_i y_i^T \tag{21}$$

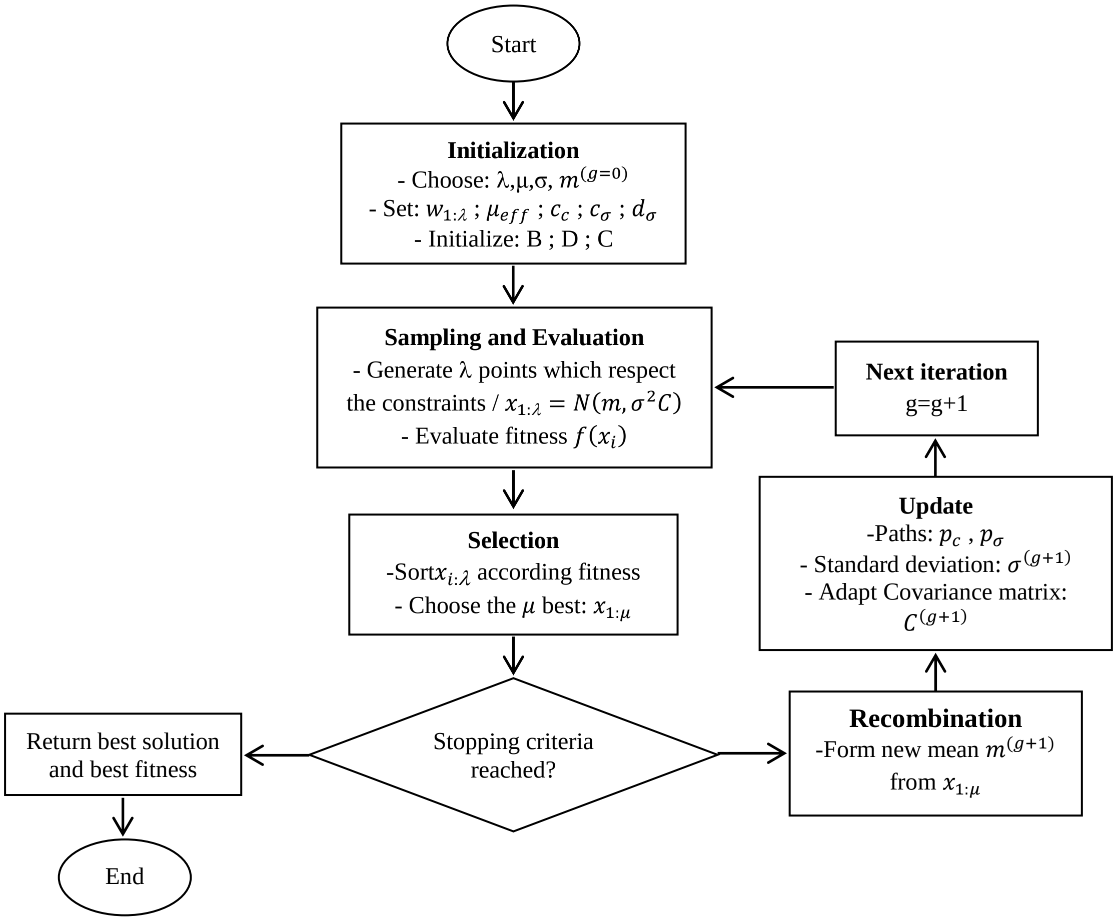

Fig. 3 Flowchart of CMA-ES algorithm

III. SIMULATIONS USING MATLAB SIMULINK, RESULTS AND DISCUSSIONS

3.1- Simulations and results

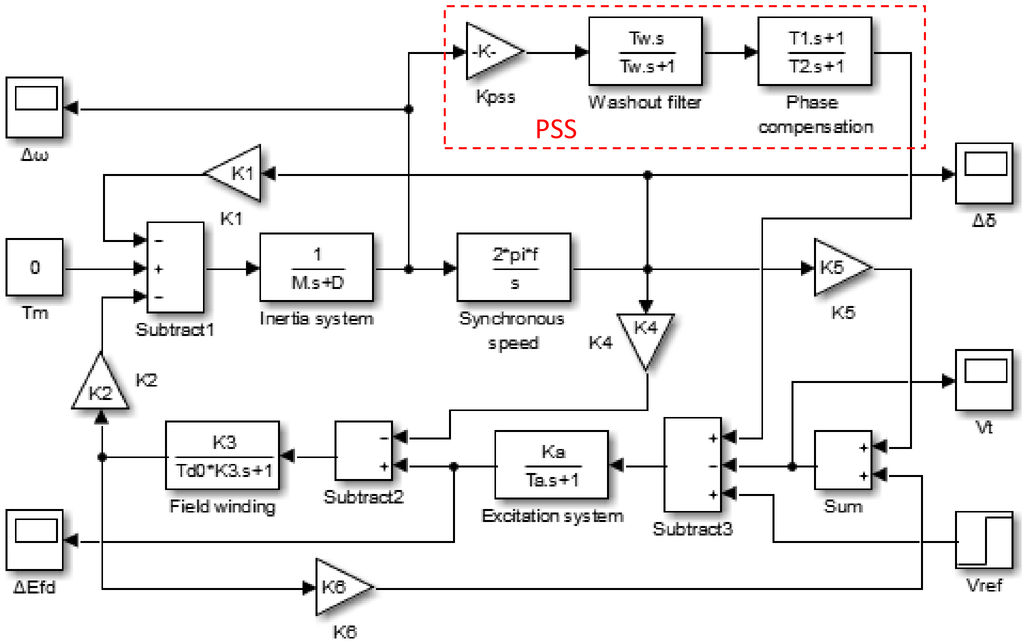

Fig. 4 Heffron-Philips model of the synchronous machine with PSS

All the simulations in this paper were carried out using Matlab m-file and Simulink.
The parameters K1 to K6 are presented in Table 1.

Table 1 SMIB parameter values K1-K6

Designation of parameters	Value
K1	1.3160
K2	0.9277
K3	0.3511
K4	0.8895
K5	−0.0702
K6	0.4321

The analysis proceeds with the following three scenarios:
Scenario 1: The parameters in Table 1 are applied to the SMIB model from the matrix (5), and the resulting eigenvalues are presented in Table 2.

Table 2 Eigenvalue results of a system without PSS

Eigenvalues	Damping Ratio
0.5233 +12.8907i	-0.0406
0.5233 -12.8907i	-0.0406
-10.8431 +17.1655i	0.5341
-10.8431 -17.1655i	0.5341

Subsequently, a PSS is added to the SMIB system, and two different methods are used to determine the PSS parameters:
Scenario 2: The PSS parameters are obtained using the phase compensation method.
Scenario 3: The PSS parameters are determined through optimization using the CMA-ES algorithm.
The global minimum is obtained at the 48th iterations, the evolution of the objective function over iterations is provided in Fig. 5.
The PSS parameters of scenario 2 and 3 are show in Table 3

Table 3 Results of PSS Parameters by computing and CMA-ES Method

Method	K_{PSS}	T_1	T_2
Phase compensation	1.6430	0.3834	0.0500
CMA-ES optimization	4.4072	0.2000	0.0500

The eigenvalues of the system with PSS, whose parameters were obtained using the two methods, are presented in Tables 4 and 5, respectively.

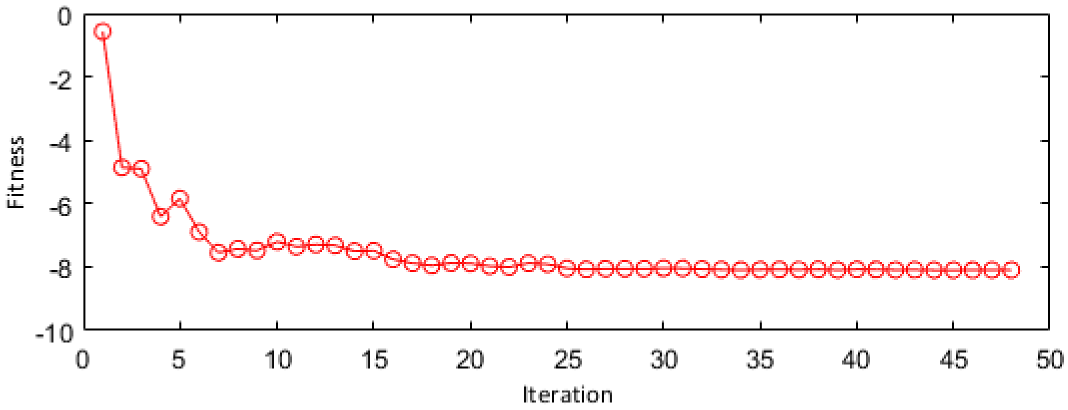

Fig. 5 Fitness depending on the iteration

Table4: Eigenvalue results with a PSS computed by phase compensation

Eigenvalues	Damping Ratio
-5.6594 +18.3834i	0.2942
-5.6594 -18.3834i	0.2942
-2.3604 +12.0500i	0.1922
-2.3604 -12.0500i	0.1922
-24.5998 + 0.0000i	1.0000

Table5: Eigenvalue results with a PSS optimized by CMA-ES

Eigenvalues	Damping Ratio
-3.7666 +19.3508i	0.1911
-3.7666 -19.3508i	0.1911
-3.7666 +11.1301i	0.3206
-3.7666 -11.1301i	0.3206
-25.5732 + 0.0000i	1.0000

The model illustrated in Fig.4 is used to simulate the three scenarios and analyze the behavior of the following variables: angular speed variation, rotor angle, field voltage,terminal voltage of the synchronous generator. The results for these three scenarios are shown in Fig.6 to 9.

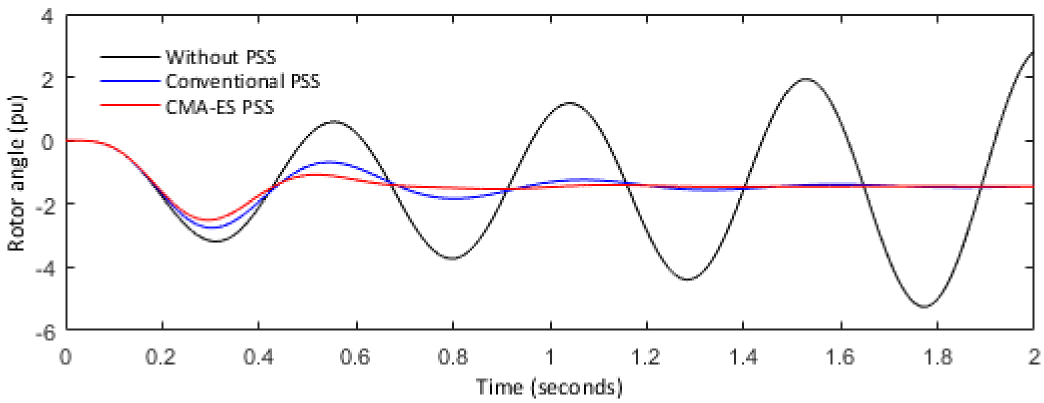

Fig. 6 Dynamic response of the rotor angle

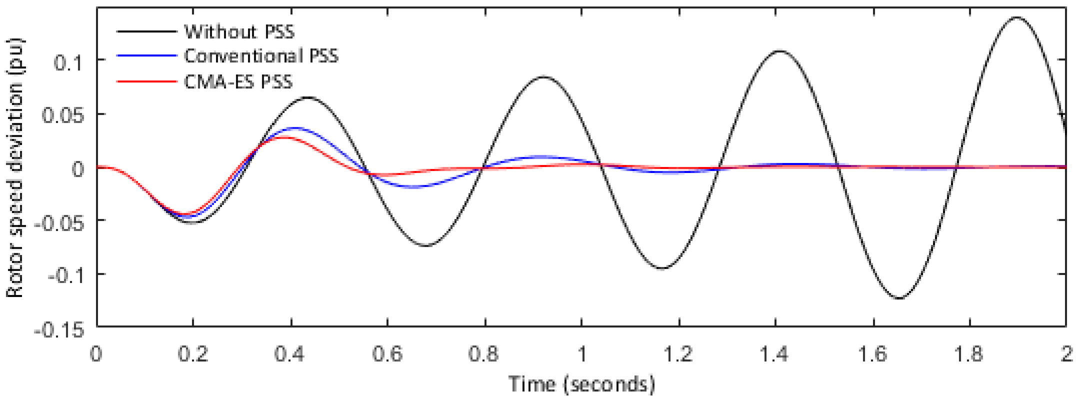

Fig. 7 Dynamic response of the rotor speed deviation

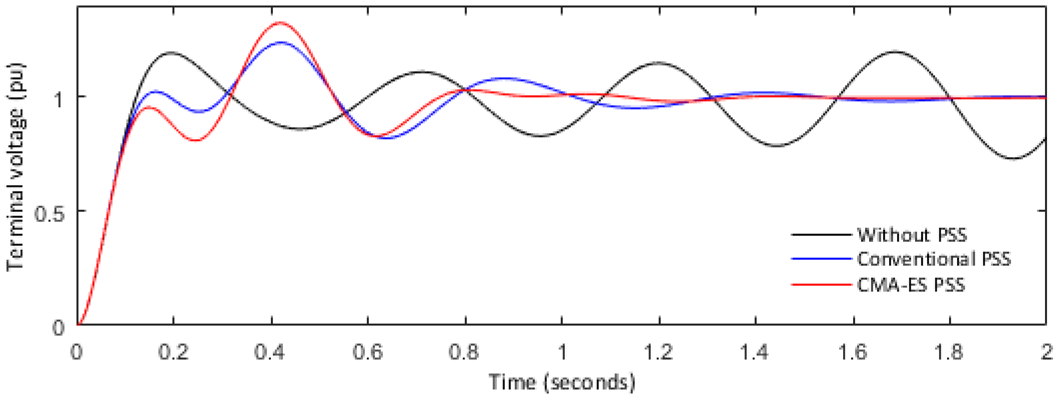

Fig. 8 Terminal voltage

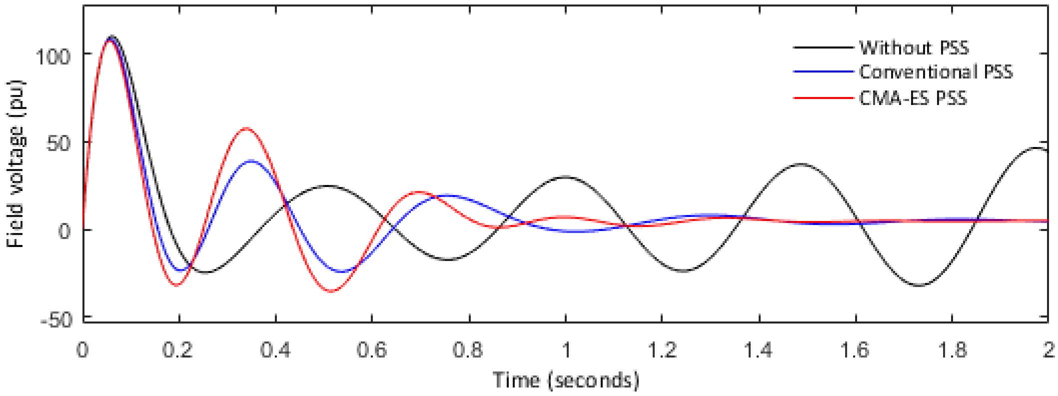

Fig. 9 Dynamic response of the field voltage

3.2-Discussion

- It can be observed from Fig. 6 to 9 that the system without a Power System Stabilizer (PSS) is unstable.
- Fig. 6 and 7 demonstrate that the system equipped with an optimized PSS exhibits superior performance in stabilizing the rotor angle and speed deviation by minimizing oscillations in a shorter time compared to the results obtained with the conventional PSS.
- According to Fig. 8, the system with the optimized PSS shows an overshoot in the terminal voltage of the synchronous generator compared to the system with the conventional PSS. However, the damping of oscillations is faster with the optimized PSS.
- Fig. 9 reveals that the excitation voltage signal appears poorly damped with the optimized PSS. This behavior is logical because the optimized PSS injects stronger oscillatory corrections to stabilize the rotor oscillations. These significant oscillations are necessary to enhance the overall stability of the system.
- The eigenvalue results for the system without a PSS shown in Table 2, indicate two eigenvalues with positive real parts, which explain the instability observed in Fig. 6 to 9. This is due to the fact that the system model was linearized around an unstable operating point.

- When comparing the dominant modes of the system with the conventional PSS (Table 4) to those of the system with the optimized PSS (Table 5), it is observed that the dominant mode of the system with the conventional PSS is closer to the imaginary axis than that of the system with the optimized PSS. This indicates that the oscillation in the system with the conventional PSS is less damped than in the system with the optimized PSS.
- If we compare the damping ratios, it is observed that their minimum values are identical to within 10^{-2}. However, considering the average of these ratios, the system with the optimized PSS exhibits a higher average damping ratio than the system with the conventional PSS. This explains why the damping performance of the optimized PSS is superior to that of the conventional PSS.

IV. CONCLUSION

In this paper, we analyzed a linearized Single Machine Infinite Bus (SMIB) model, known as the Heffron-Phillips model, with the integration of a Power System Stabilizer (PSS) to mitigate transient oscillations. Two approaches were employed to determine the PSS parameters: the conventional phase compensation method and the CMA-ES optimization method. The latter approach utilized a well-defined objective function and constraints to ensure effective optimization. The proposed approach was verified through various analyses, including eigenvalue analysis, damping ratio assessment, and time-domain simulation results. Results demonstrated that the PSS parameters derived via CMA-ES optimization significantly enhanced the damping of oscillations across all system variables, achieving rapid stabilization. These findings highlight the potential of CMA-ES as a reliable tool for improving power system stability. Future work could extend this approach to more complex power systems, such as multi-machine networks.

REFERENCES

[1]. A.-R. S. A. Ali, K. R. Daud, [2019], « Mitigation of SMIB Oscillations Using PSS Based onParticle Swarm Optimization Algorithm », Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[2]. M. Shafiullah, M. J. Rana, M. A. Abido, [2017] « Power System Stability Enhancement ThroughOptimal Design of PSS Employing PSO », Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[3]. M. O. Hassan, S. J. Cheng, [2010] « Optimization of Conventional Power System Stabilizer to Improve Dynamic Stability », Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[4]. P. W. Sauer and M. A. Pai , « Power system dynamics and stability », University of Illinois at Urbana-Champaign.

[5]. P. Valand, M. Gohil, A. Rabari, J. Prajapati, [2014] « A Novel approach for tuning of Power System Stabilizer (SMIB system) using Genetic Local Search Technique » International Journal for Scientific Research & Development, www.ijsrd.com.

[6]. B. Rout , B.B. Pati , A. Pattnaik, [2018] « Small Signal Stability Enhancement of Power System with GA Optimized PD type PSS and AVR Control » Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[7]. H. Aliyari1, R. Effatnejad, H. Tadayyoni, A. Aryaei, [2013] « Design of Power System Stabilizer with PSO for Heffron-Phillip's Model » Journal of Engineering and Architecture.

[8]. A. Kahouli,.T. Guesmi, H. H. Abdallah and A. Ouali, [2009] « A genetic algorithm PSS and AVR controller for electrical power system stability »,Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[9]. S. Keskes, N. Bouchiba , S. Sallem, L. Chrifi-Alaoui and M.B.A Kammoun, [2017] « Optimal tuning of power system stabilizer using genetic algorithm to improve power system stability »,Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[10]. P. W. Pande, S. Chakrabarti, and S. C. Srivastava, [2018] « Online Updating of Synchronous Generator Linearised Model Parameters and PSS Tuning »,Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[11]. Sheshnarayan, B.Verma and P. K.Padhy, [2019] « Design PID Controller based PSS using Cuckoo Search Optimization Technique », Institute of Electrical and Electronics Engineers, ieeexplore.ieee.org.

[12]. P. P. Kumar, M. R. Babu, Saraswathi, [2012], « Dynamic analysis of Single Machine Infinite Bus system using Single input and Dual input PSS » International Electrical Engineering Journal.

[13]. J. J. Schneider, S. Kirkpatrick, [2006] « Overview of Stochastic Optimization Algorithms » Springer, link.springer.com.

[14]. D. Fouskakis, D. Draper, [2002] « Stochastic Optimization: a Review » International Statistical Review.

[15]. N. Hansen, [2023] « The CMA Evolution Strategy: A Tutorial », https://doi.org/10.48550/arXiv.1604.00772

[16]. O. Krause, T. Glasmachers, [2015] « A CMA-ES with Multiplicative Covariance Matrix Updates », Association for Computing Machinery Journal, dl.acm.org.

[17]. N. Hansen, [2006] « The CMA Evolution Strategy: A Comparing Review », Springer, link.springer.com.